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Original Article

# Volatility spillovers between crude oil price and Vietnamese sectoral equity markets: Evidence from a frequency dynamics perspective

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**Abstract:** This article aims to examine the volatility spillovers between crude oil and the Vietnamese stock market, focusing on sector-level dynamics within an emerging economy context. Using stock index data from sixteen sectors, the study employs the time-frequency connectedness framework developed by Baruník and Krehlík (2018) to assess the interdependence between the crude oil market and Vietnamese equities across different time horizons. The results indicate a strong volatility spillover between the two markets, suggesting a shared risk exposure. Among sectors, the technology industry is identified as the most significant transmitter of volatility, while the airline sector exhibits the lowest degree of connectedness. Moreover, the total connectedness index fluctuates notably over time, pointing to the influence of macroeconomic and geopolitical factors. These findings provide critical insights for investors and policymakers by highlighting the importance of sector-specific sensitivity and broader market interactions in shaping investment strategies and managing financial risk.

*Keywords:* Volatility, crude oil price, equity markets, Vietnam.

## 1. Introduction

Crude oil remains a fundamental resource for modern industrial economies, including Vietnam. Between 2000 and 2023, domestic gasoline consumption increased markedly, rising from 5.8 million liters in 2000 to 22.6 million liters in 2020, driven by economic growth, industrialization, vehicle ownership, and transport demand. Although future patterns may shift with energy policies, price dynamics, and alternative energy adoption, the persistent upward trend underscores Vietnam's vulnerability to global oil price shocks, which significantly affect its economy and stock market. Oil price fluctuations strongly influence stock price volatility by shaping both macroeconomic conditions and firm-level performance. According to supply and demand theory, changes in oil prices alter production costs, particularly in manufacturing and transportation, thereby affecting profit margins and stock valuations (Hamilton, 2009). The efficient market hypothesis suggests that such information is rapidly reflected in stock prices, creating volatility as markets adjust (Fama, 1970). Real options theory further highlights how oil price uncertainty delays or reshapes investment decisions, impacting firm value (Dixit & Pindyck, 1994). Moreover, oil price

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shifts drive inflation and interest rates, influencing economic growth, investor sentiment, and financial stability (Barsky & Kilian, 2004). This interplay emphasizes the central role of energy prices in global financial markets.

Since Vietnam has made significant national efforts to improve its economy through reforms and investments, such as the Doi Moi economic reforms of 1986, and joining many free trade agreements, it has garnered considerable attention from international investors. These efforts have significantly impacted the world's energy and financial markets. This raises an important question: How do the volatility of the international crude oil market and the Vietnamese stock markets interact?

Despite extensive research on the link between crude oil prices and stock market performance, limited attention has been paid to emerging economies like Vietnam, especially at the sectoral level. Most studies focus on aggregate indices or developed markets, overlooking heterogeneous industry responses within a single economy. In addition, prior research has largely relied on time-domain methods, which may not fully capture the complex and dynamic nature of volatility transmission across different investment horizons. This creates a gap in understanding how oil price shocks affect Vietnamese industries over both short- and long-term frequencies.

To address this gap, this study applies a frequency dynamics approach to examine volatility spillovers between crude oil and sector-specific equity indices in Vietnam. Specifically, we employ the time-frequency coupling method of Baruník and Křehlík (2018), an extension of Diebold and Yilmaz's (2012) connectedness index. This method allows simultaneous assessment of the magnitude and direction of spillovers across time and frequencies. Econometrically, it captures time variation in connectedness while decomposing it across frequency domains, thereby identifying which horizons most contribute to volatility transmission within the system.

The study makes several key contributions. First, it is among the first to analyze volatility spillovers between the crude oil market and Vietnam's stock market, emphasizing the cyclicality of spillovers across different response frequencies. By distinguishing between short- and long-term effects, it offers a clearer understanding of financial market dynamics. Second, by focusing on sectoral indices rather than aggregate measures, it provides a more granular view of market linkages, useful for portfolio diversification and risk management. Third, it incorporates the role of structural shifts, such as political instability and economic crises, in amplifying volatility and contagion, as highlighted by Vietnam's sharp stock market decline after the Russia-Ukraine war. Finally, the study demonstrates that oil shocks are critical drivers of both short- and long-term volatility spillovers, enhancing forecasting accuracy and informing strategies to mitigate market uncertainty.

## 2. Literature review

A large body of research examines the relationship between oil prices and stock returns (Broadstock & Filis, 2014; Degiannakis et al., 2013), with more recent studies focusing on volatility spillovers and contagion effects (Malik & Hammoudeh, 2007; Arouri et al., 2012; Awartani & Maghyereh, 2013; Khalfaoui et al., 2015; Ewing & Malik, 2016; Wang & Wu, 2018). Methodologically, these works apply models such as Engle's DCC (2002), Engle and Kroner's BEKK-GARCH (1995), VAR-GARCH (Ling & McAleer, 2003), EGARCH, and the spillover index based on variance decomposition (Diebold & Yilmaz, 2012, 2014). Much of the literature focuses on aggregate stock indices, highlighting linkages between global oil and the US or oil-rich markets (Malik & Hammoudeh, 2007; Awartani & Maghyereh, 2013), spillovers to the US (Ewing & Malik, 2016; Phan et al., 2016), G7 economies (Khalfaoui et al., 2015), and broader contagion patterns (Maghyereh et al., 2016; Wang & Wu, 2018). However, sectoral studies show that responses differ across industries: Malik and Ewing (2009) find significant volatility transmission to five US stock sectors; Arouri et al. (2011) demonstrate heterogeneous effects depending on oil intensity; and Arouri et al. (2012) together with Haddow et al. (2013) emphasize sector-specific impacts on costs, growth, and confidence. Further, Bouri et al. (2016) and Tiwari et al. (2018) reveal that spillovers vary by the nature of oil shocks, distinguishing between demand- and supply-driven effects.

All of the above studies highlight the drivers of linkages between oil prices and stock markets but overlook the frequency dynamics of transmission that vary across horizons. Long-term shocks generate high energy at low frequencies, leading to persistent spillovers across markets, while short-term shocks trigger temporary contagion, deviating prices from long-run trends. For instance, Balke and Wohar (2002) and Ortu et al. (2013) show that permanent changes in dividend expectations produce lasting stock market effects, whereas temporary fiscal policy adjustments influence markets only in the short run. These shocks propagate through markets with distinct frequency responses.

To capture this, we employ the time-frequency connectedness framework developed by Krehlík and Baruník (2017), Ferrer et al. (2018), and Baruník and Krehlík (2018). Prior studies applied this method to oil-based commodities or renewable energy stocks, but not oil–stock market linkages. Our study extends the approach by analyzing sector-specific stock index data in Vietnam, uncovering the frequency dynamics of volatility spillovers between oil and equities. We further assess how structural breaks in volatility shape risk transmission and examine whether frequency spillovers can improve predictions of future market uncertainty.

## 3. Empirical methodology

*3.1. Spillover measures in the time domain*

Our starting point is Sims's (1980) vector autoregression model:

$$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \cdots + \Phi_p X_{t-p} + \epsilon_t \quad (1)$$

where $X_t = (X_{1t}, X_{2t}, \dots, X_{nt})'$ is an n-dimensional vector containing the movements of n market indices, $\epsilon_t$ is the white noise with the covariance matrix $\sum$ and $\Phi_1, \dots, \Phi_2$ are the matrices coefficient match. Each variable is regressed on its own and others' $p$ lags. It is useful to work with n × n matrix lag-polinomial $\Phi(L) = \left[I_n - \Phi_1 L - \cdots - \Phi_p L^p\right]$ with $I_n$ the identity matrix, since the model can be written briefly as $\Phi(L)X_t = \epsilon_t$

We can rewrite the equation (1) as an infinite moving average process:

$$X_t = \psi(L)\epsilon_t. \quad (2)$$

where the matrix $\psi(L)$ of infinitely lagged polynomials can be computed recursively from $\Phi(L) = [\psi(L)]^{-1}$. Moving average performance is crucial for computing generalized forecast error variance decomposition (FEVD) and understanding system dynamics, written as:

$$(\Theta_H)_{k,j} = \frac{\sum_{j,j}^{-1} \sum_{h=0}^{H} ((\psi_h \Sigma)^{2}}{\sum_{h=0}^{H} (\psi_h \Sigma \psi'_h)_{k,k}} \quad (3)$$

where $H$ is the forecast horizon. This separation measures Fractions of H-step-ahead error variance in volatility forecasting in market $k$ due to shocks to market volatility $j$.

The spillover measure is the share of variance in the forecast attributed to external factors, calculated as the ratio of non-diagonal elements to the total matrix sum (Diebold & Yilmaz, 2012):

$$S^H = \frac{\sum_{k=1,k\neq j}^{n} (\tilde{\Theta}_H)_{k,j}}{\sum_{k,j} (\tilde{\Theta}_H)_{k,j}} = 1 - \frac{\sum_{k=1}^{n} (\tilde{\Theta}_H)_{k,k}}{\sum_{k,j} (\tilde{\Theta}_H)_{k,j}} \quad (4)$$

where $(\tilde{\Theta}_H)_{k,j}$ are the standardized effects denoted as

$$(\tilde{\Theta}_H)_{k,j} = \frac{(\Theta_H)_{k,j}}{\sum_{j=1}^{n} (\Theta_H)_{k,j}} \quad (5)$$

It is clear that $S^H$ measures the overall volatility spillover over the whole system, and $(\tilde{\Theta}_H)_{k,j}$ measures how volatility spreads from market $j$ to market $k$.

Furthermore, important insights can be obtained from the pairwise network pervasive, which we define as

$$S_{k,j}^{H} = (\tilde{\Theta}_H)_{j,k} - (\tilde{\Theta}_H)_{k,j} \quad (6)$$

The net pairwise volatility spillover between markets k and j is simply the difference between compound volatility shocks transmitted from market k to market j and shocks transmitted from j to k.

*3.2. Spillover measures in the frequency domain*

Recent studies highlight that financial–commodity linkages differ in persistence (Barunik et al., 2015; Dew-Becker & Giglio, 2016). Spectral methods, particularly generalized FEVD (GFEVD), analyze connectivity through frequency response functions.

$$S_X(\omega) = \sum_{h=-\infty}^{\infty} E(X_t X_{t-h}) e^{-i\omega h} = \psi(e^{-i\omega}) \sum \psi'(e^{+i\omega}) \quad (7)$$

where $\psi(e^{-i\omega}) = \Sigma_h e^{-i\omega h} \psi_h, h = 1, \dots, H,$ can be obtained as a Fourier transform of the coefficients $\psi_h$, with $i = \sqrt{-1}$. The power spectrum $S_X(\omega)$, derived from the Fourier transform of $\psi_h$ , describes how the variance of $X_t$ is distributed across frequencies. Based on this observation, the GFED over frequency $\omega$ can be expressed as

$$(\Theta(\omega))_{k,j} = \frac{\sum_{j,j}^{-1} \left|(\psi(e^{-i\omega})\Sigma)_{k,j}\right|^2}{(\psi(e^{-i\omega})\Sigma\psi'(e^{+i\omega}))_{k,k}} \quad (8)$$

*3.3. Data collection*

This study examines the relationship between crude oil prices and stock indexes, using West Texas Intermediate (WTI) futures contracts from the New York Mercantile Exchange and stock price indexes from 16 major Vietnamese industries from January 2010 to May 2023. Monthly returns are computed from log changes, with volatility estimated from daily high, low, open, and close prices, following Alizadeh et al. (2002) and Diebold and Yilmaz (2009).

$$\tilde{\sigma}^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2 \quad (9)$$

where H denotes the monthly high, L the monthly low, O the opening price on the first day, and C the closing price on the last day (all in natural logarithms).

## 4. Empirical results

*4.1. Descriptive statistics*

Table 1 shows that crude oil exhibits greater volatility than Vietnam's sixteen sectoral stock markets, with skewness and kurtosis indicating heterogeneous dynamics across sectors. All descriptive values are positive, reflecting volatility persistence. Figure 1 further reveals limited multicollinearity, as no correlation exceeds 0.7. While most sectors are positively correlated, airlines display negative correlations with technology, petroleum, tourism, minerals, agriculture, and media, and insurance with tourism and media, suggesting sector-specific volatility linkages.

*4.2. Results of the generalized forecast error variance decomposition (FEVD)*

*4.2.1. Average connectedness measures*

During the study period, the technology sector generated the strongest spillovers to other industries (106.48 per cent), followed by agriculture (104.01 per cent) and construction (103.19 per cent), while airlines (26.75 per cent), retail (40.5 per cent), postal services (40.46 per cent), and tourism (14.76 per cent) were least affected, with others ranging from 56.5 per cent to 94.6 per cent. In terms of external influence "FROM" others, securities faced the highest connectedness (80.38 per cent), whereas airlines recorded the lowest (51.69 per cent), reflecting relative stability. "NET" connectedness further shows that retail, insurance, petroleum, postal services, tourism, airlines, minerals, banking, and healthcare acted as net volatility receivers, while technology, securities, logistics, electricity, agriculture, media, and construction emerged as net transmitters.

Table 1: Summary statistics of the variables under examination

| | mean | median | standard deviation | min | max | skew | kurtosis | JB | ADF |
|---|---|---|---|---|---|---|---|---|---|
| retail | 0.010997 | 0.008026 | 0.010964 | 0.000532 | 0.083732 | 3.555242 | 17.80229 | 2549.6*** | -10.68*** |
| insurance | 0.019021 | 0.011797 | 0.020877 | 0.000503 | 0.11437 | 2.23471 | 5.43075 | 344.22*** | -9.324*** |
| security | 0.022009 | 0.014357 | 0.023897 | 0.001035 | 0.138879 | 2.559336 | 8.092706 | 637.47*** | -8.775*** |
| technology | 0.015743 | 0.008245 | 0.024031 | 0.000217 | 0.210272 | 4.904406 | 30.71585 | 7205.4*** | -10.94*** |
| petroleum | 0.021883 | 0.015533 | 0.023107 | 0.000121 | 0.143347 | 2.733102 | 8.974738 | 767.38*** | -9.535*** |
| postal | 0.040247 | 0.013284 | 0.079801 | 0 | 0.743222 | 5.469747 | 39.62031 | 11705*** | -11.96*** |
| logistic | 0.010883 | 0.00623 | 0.014122 | 0.000176 | 0.124259 | 4.572182 | 28.74147 | 6305.5*** | -10.67*** |
| electricity | 0.006606 | 0.004686 | 0.005395 | 0.000137 | 0.026446 | 1.456876 | 1.760305 | 80.73*** | -9.899*** |
| tourism | 0.014883 | 0.005913 | 0.032688 | 3.54E-06 | 0.332437 | 6.587447 | 55.08804 | 22220*** | -10.44*** |
| airline | 0.022249 | 0.009776 | 0.028996 | 0 | 0.15292 | 2.236185 | 4.954451 | 309.93*** | -11.19*** |
| mineral | 0.01686 | 0.010797 | 0.023353 | 0.000375 | 0.222383 | 4.912737 | 35.85949 | 9579.7*** | -9.537*** |
| bank | 0.0117 | 0.007302 | 0.012187 | 0.000263 | 0.066006 | 2.275322 | 5.752976 | 374.36*** | -9.165*** |
| agriculture | 0.013481 | 0.008964 | 0.014409 | 0.000441 | 0.09378 | 2.833618 | 9.553625 | 857.28*** | -10.19*** |
| media | 0.008772 | 0.005946 | 0.009611 | 8.52E-05 | 0.049808 | 2.227393 | 5.216518 | 327.43*** | -7.543*** |
| construction | 0.013432 | 0.009137 | 0.012594 | 0.000773 | 0.075252 | 2.0913 | 5.02791 | 297.8*** | -9.868*** |
| medical | 0.006746 | 0.005068 | 0.005869 | 0.000636 | 0.032425 | 1.911363 | 3.815027 | 203.15*** | -10.83*** |
| WTI | 0.019473 | 0.011734 | 0.034309 | 0.000944 | 0.384276 | 7.909513 | 77.91458 | 19494*** | -4.404*** |

*Note*: *, ** and *** represent significance at 10 per cent, 5 per cent, and 1 per cent, respectively.
Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ADF: Dickey and Fuller (1979)

*Source*: Author's own synthesis.

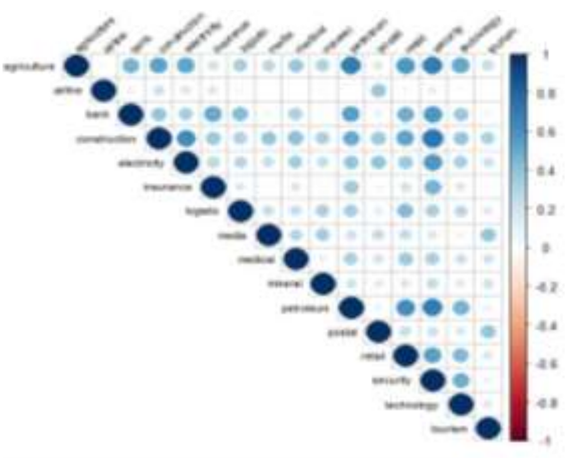

Figure 1: Visualization of correlation matrix

*Source*: Author's own synthesis.

The net volatility spread results show that retail, insurance, petroleum, postal, tourism, airline, mineral, bank, and medical consistently receive net volatility spread. These industries depend on consumer demand and market stability, making them sensitive to economic fluctuations, exchange rates, interest rates, inflation, and national policies. Each sector has unique risks—insurance faces loss ratio changes, petroleum is affected by global crude prices, and aviation, tourism, mining, and banking deal with competition and operational costs. External factors like government regulations, trade policies, geopolitical events, technology, and consumer trends further contribute to volatility. These findings are consistent with Mensi et al. (2021), who found that in the U.S. market, sectors such as energy, financials, and utilities often act as net receivers of volatility under normal market conditions, reinforcing the idea that structurally important sectors tend to absorb systemic risk from other parts of the economy.

The study reports a high Total Connectedness Index (TCI) of 70.35 per cent, indicating strong inter-industry volatility linkages, consistent with prior research. This suggests that even under normal conditions, industry volatilities significantly influence one another, underscoring the role of portfolio diversification in risk mitigation. The result aligns with Choi (2022), who found a Total Spillover Index (TSI) of 76.4 per cent across 24 Vietnamese sectors (2012–2021) and noted spillovers nearing 90 per cent during COVID-19, confirming heightened interlinkages during uncertainty.

*4.2.2. Dynamic total connectedness index*

While average outcomes give a broad view of volatility interdependencies, the time-varying Total Connectedness Index (TCI) offers deeper insight. Figure 2 shows spillovers peaking above 80 per cent in late 2010, then declining through 2011–2018 with spikes in 2012 and 2017, before falling to about 50 per cent in 2019 amid U.S.–China trade tensions and the Saudi Aramco attack. The index surged above 70 per cent in 2020, stabilized in 2020–2021, and rose again in 2022, driven by higher oil prices, global uncertainty, and regulatory changes. From late 2022 to May 2023, volatility spillovers rose further due to persistently high oil prices, the European embargo on Russian oil, Western sanctions, and rebounding global demand during the Russia–Ukraine conflict. These findings align with Zhao et al. (2024), who showed geopolitical shocks amplify energy market risks.

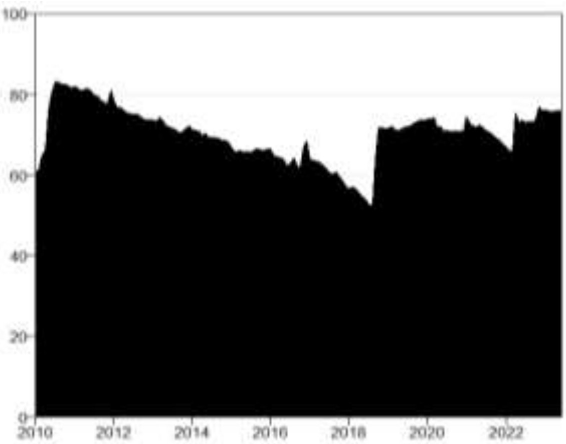


Figure 2: Dynamic total connectedness

*Notes*: Figure 3 shows the time-varying total connectedness index of 16 industry price indices, estimated via GFEVD from a TVP-VAR model with 10-step forecasts, using lags selected by BIC over January 2010–May 2023.

*Source*: Author's own synthesis.

*4.2.3. Dynamic net directional connectedness*

Figure 3 presents the time-varying net directional connectedness from each industry to all others, supplementing the results in Table 2. The sixteen industries analyzed are categorized into three groups: shock transmitters, industries with dual roles in shock transmission and reception, and shock receivers during 2010-2014.

The first group—technology, electricity, agriculture, and construction—primarily function as shock transmitters, contributing consistently to stock market volatility despite occasional disruptions. Technology remained a net transmitter from 2014 to 2017 before a shock in 2017 linked to data breaches, such as BIDV customer information leaks and ZaloPay security issues. Electricity also transmitted volatility but faced mild shocks in 2017 and 2019 from extreme weather events. Agriculture and construction, though generally transmitters, became receivers between 2016 and 2019 due to environmental incidents, climate change, and regulatory shifts that disrupted production and projects. These findings align with Lou et al. (2024), who applied a TVP-VAR model, identified materials, energy, and industrial sectors as significant net transmitters of volatility in the Chinese market, especially during periods of economic and political upheaval. Their study underscores the role of these sectors in propagating shocks across the financial system.

The second group—logistics, media, securities, minerals, retail, petroleum, and banking—alternated between transmitting and receiving shocks. Logistics shifted from a transmitter (2010–2019) to a recipient after COVID-19 disrupted supply chains. Media moved from transmitter to recipient after 2016 amid regulatory changes and competition from social platforms. Securities became a strong transmitter after 2018, supported by foreign capital inflows and digitalization, while minerals, though mainly receivers, briefly transmitted shocks during 2017–2019 due to investment-driven efficiency gains. Retail acted as a transmitter from 2018 to 2021, driven by rising incomes and infrastructure growth. Petroleum also emerged as a net transmitter (2021–2023), reflecting geopolitical crises such as the U.S. pipeline attack and Russia–Ukraine war. Similarly, banking transitioned into a transmitter during the post-pandemic recovery, supported by asset growth and digital transformation.

Table 2: Summary statistics of the average connectedness measures

| zz | retail | insurance | security | technology | petroleum | postal | logistic | electricity | tourism | airline | mineral | bank | agriculture | media | construction | medical | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **retail** | 27.74 | 3.14 | 6.99 | 9.53 | 7.23 | 3.09 | 4.28 | 3.72 | 2.84 | 1.53 | 3.66 | 6 | 7.23 | 2 | 5.97 | 5.03 | 72.26 |
| **insurance** | 3.59 | 33.37 | 8.13 | 3.21 | 5.74 | 1.27 | 4.98 | 5.91 | 1.43 | 2.92 | 2.45 | 11.53 | 3.85 | 1.71 | 6.63 | 3.28 | 66.63 |
| **security** | 4.62 | 2.91 | 19.62 | 9.49 | 6.56 | 2.44 | 5.57 | 8.07 | 1.99 | 1.27 | 2.74 | 7.48 | 8.01 | 3.85 | 11.78 | 3.61 | 80.38 |
| **technology** | 3.35 | 2.1 | 6.77 | 28.76 | 4.6 | 1.9 | 7.61 | 5.5 | 4.64 | 0.85 | 5.69 | 3.21 | 11.52 | 2.72 | 8.09 | 2.69 | 71.24 |
| **petroleum** | 6.3 | 3.94 | 9.25 | 8.12 | 24.31 | 1.38 | 6.64 | 6.06 | 1.54 | 0.67 | 2.49 | 6.15 | 10.6 | 2.65 | 6.44 | 3.46 | 75.69 |
| **postal** | 4.23 | 1.61 | 3.29 | 4.85 | 2.43 | 40.25 | 4.06 | 7.44 | 3.38 | 3.83 | 2.55 | 2.14 | 4.09 | 6.36 | 6.9 | 2.59 | 59.75 |
| **logistic** | 3.98 | 2.82 | 4.4 | 8.56 | 5.3 | 3.07 | 26.38 | 8.74 | 2.43 | 2.3 | 4.97 | 5.15 | 7.44 | 5.66 | 5.69 | 3.1 | 73.62 |
| **electricity** | 2.87 | 2.18 | 6.97 | 6.34 | 5.07 | 4.91 | 8.81 | 25.77 | 2.38 | 3.58 | 3.1 | 4.32 | 7.1 | 4.77 | 7.91 | 3.9 | 74.23 |
| **tourism** | 2.96 | 1.26 | 3.64 | 9.35 | 1.35 | 2.71 | 3.94 | 4.2 | 31.5 | 2.93 | 8.81 | 1.78 | 7.15 | 6.98 | 7.36 | 4.08 | 68.5 |
| **airline** | 2.5 | 5.79 | 2.86 | 2.87 | 1.64 | 5.22 | 4.24 | 3.22 | 5.9 | 48.31 | 2.45 | 2.6 | 4.79 | 3.49 | 2.42 | 1.69 | 51.69 |
| **mineral** | 2.61 | 1.35 | 4.49 | 6.37 | 3.47 | 1.77 | 3.56 | 4.56 | 6.08 | 0.85 | 35.39 | 2.63 | 7.32 | 9.56 | 6.7 | 3.29 | 64.61 |
| **bank** | 4.7 | 6.36 | 9.69 | 5.22 | 7.46 | 1.05 | 7.56 | 6.36 | 1.39 | 1.34 | 1.2 | 28.66 | 4.79 | 4.75 | 4.81 | 4.66 | 71.34 |
| **agriculture** | 4.25 | 1.83 | 7.84 | 11.54 | 7.14 | 1.82 | 7.18 | 6.41 | 4.09 | 0.95 | 5.31 | 3.94 | 22.04 | 4.56 | 7.2 | 3.92 | 77.96 |
| **media** | 2.34 | 1.03 | 3.84 | 7.1 | 2.93 | 4.74 | 6.08 | 5.06 | 4.76 | 1.36 | 7.01 | 3.24 | 6.65 | 29.49 | 7.92 | 6.47 | 70.51 |
| **construction** | 3.78 | 2.54 | 10.82 | 9.56 | 4.82 | 3.83 | 5.52 | 7.39 | 3.98 | 1.29 | 4.46 | 4.09 | 7.24 | 4.99 | 20.95 | 4.74 | 79.05 |
| **medical** | 5.5 | 1.63 | 5.62 | 4.37 | 4.33 | 1.26 | 4.36 | 4.94 | 4.04 | 1.08 | 3.03 | 5.65 | 6.23 | 8.7 | 7.37 | 31.89 | 68.11 |
| **TO** | 57.57 | 40.5 | 94.6 | 106.48 | 70.07 | 40.46 | 84.4 | 87.58 | 50.86 | 26.75 | 59.92 | 69.91 | 104.01 | 72.75 | 103.19 | 56.5 | 1125.56 |
| **Inc.Own** | 85.32 | 73.87 | 114.22 | 135.24 | 94.38 | 80.71 | 110.78 | 113.35 | 82.36 | 75.07 | 95.32 | 98.57 | 126.05 | 102.24 | 124.14 | 88.39 | cTCI/TCI |
| **NET** | -14.68 | -26.13 | 14.22 | 35.24 | -5.62 | -19.29 | 10.78 | 13.35 | -17.64 | -24.93 | -4.68 | -1.43 | 26.05 | 2.24 | 24.14 | -11.61 | 75.04/70.35 |

*Notes*: This table reports total, directional, and pairwise spillovers estimated from a TVP-VAR model using GFEVD with 10-step-ahead forecasts and lag length selected by BIC, covering January 2010–May 2023. 'TO' and 'FROM' spillovers are measured by off-diagonal column and row sums, with 'NET' defined as their difference. The total spillover index, shown in the lower-right corner, represents the ratio of the grand off-diagonal sum to total variance, expressed as a percentage.

*Source*: Author's own synthesis.

The final group—tourism, airlines, medical, postal, and insurance—primarily acted as shock receivers. Tourism briefly transmitted shocks in early 2019 but became a strong recipient after COVID-19, while airlines and medical showed short transmission phases in 2016 due to expansion and healthcare reforms, respectively. Postal consistently remained a receiver amid technological and regulatory changes, and insurance was highly sensitive to external shocks given its ties to multiple sectors. These results align with Gao and Yang (2024), who, using a TVP-VAR time-frequency approach, identified tourism as a net recipient of volatility from energy and carbon markets, particularly during crises such as COVID-19 and the Russia–Ukraine conflict, underscoring the vulnerability of service-oriented sectors.

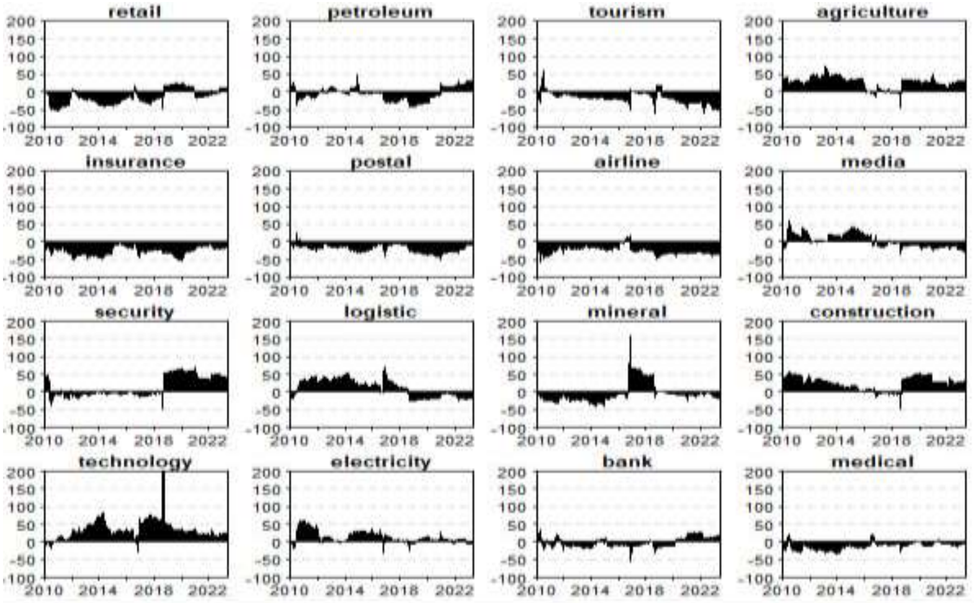


Figure 3. Dynamic net directional connectedness
*Source*: Author's own synthesis.

*4.3. Summary of the results from TVP-VAR model*

Figure 4 illustrates industry connectedness, where blue nodes denote transmitters and yellow nodes receivers, with node size reflecting average connectedness and arrow thickness indicating transmission strength. The network reveals a clear division: technology, construction, and agriculture act as primary volatility sources, with technology exerting the strongest influence through widespread spillovers driven by innovation and cross-industry digital transformation. Tourism emerges as the most affected sector, while construction and agriculture shocks particularly impact airlines and insurance. Overall, postal, insurance, airline, and tourism are net receivers, with insurance highly exposed to multiple industries and tourism especially vulnerable to economic fluctuations.

*4.4. The impact of WTI crude oil price shocks on Vietnamese sectorial stock market spillover from Wavelet coherence and phase*

The graph below uses color to denote correlation strength between WTI crude oil prices and Vietnamese sectoral stock indices—blue for weak, yellow for moderate, and red for strong. Arrows indicate causality: upward when oil prices drive stocks, downward when stocks influence oil, right-to-left for positive correlations, and left-to-right for negative correlations.

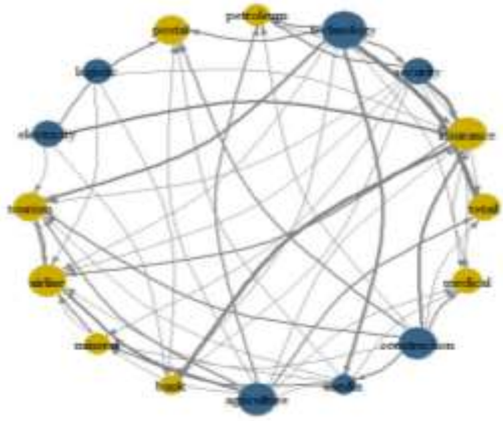

Figure 4: Network plot
Notes: Results are based on 10-step-ahead generalized forecast error variance decomposition from a TVP-VAR(2) model selected by BIC.
*Source:* Author's own synthesis.

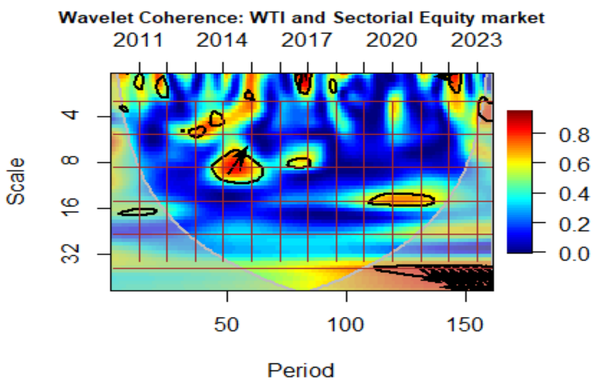


Figure 5: Wavelet Coherence: WTI crude oil and TCI of Sectorial equity market
*Source*: Author's own synthesis.

Periods of strong coherence are evident in 2014-2016 and 2020-2022, coinciding with major global disruptions. The 2014-2015 oil price collapse reduced corporate earnings and energy-related investment, while the COVID-19 pandemic heightened volatility as stock indices closely tracked crude oil prices as a proxy for recovery prospects, with demand shocks reinforcing this link. These findings align with Pham and Le (2024), who showed asymmetric effects of oil and gas price fluctuations on Vietnam's stock market during crises. Sectoral responses further reveal stronger correlations in energy and industrial sectors, where higher oil prices boost energy firm margins but raise costs for transportation and manufacturing (Nguyen & Tran, 2020). By contrast, consumer goods and financials show mixed effects, while technology and healthcare display weaker coherence given their lower energy dependence.

The causal relationship between oil prices and stock indices is time-varying. Oil shocks primarily drove stock markets in 2015-2016; feedback effects emerged in 2020-2021 as sentiment and macroeconomic expectations influenced oil prices; and by 2022, geopolitical tensions—especially the Russia–Ukraine conflict—intensified this bidirectional link. Wavelet analysis highlights volatile yet strong connections shaped by supply disruptions, sanctions, and trade imbalances. These dynamics are particularly relevant for Vietnam, where about 70 per cent of petroleum demand is imported (VietnamCredit, 2022) and oil and gas remain central to state revenue, exports, and energy security (VOV World, 2023). Global oil price fluctuations directly affect costs, input availability, and profitability in logistics, airlines, and manufacturing.

In other words, the wavelet coherence and phase analysis reveal that WTI crude oil price shocks significantly impact Vietnamese sectorial stock market movements, though the strength and direction of this relationship vary across different time periods. Sectors with direct exposure to energy costs, such as industrials and utilities, exhibit the most pronounced correlations, while other sectors display more complex responses to oil price fluctuations. Furthermore, during periods of heightened market uncertainty, the feedback effect between stock prices and oil prices becomes more apparent, reflecting broader economic sentiment and investor behavior. These findings underscore the importance of monitoring energy price dynamics as a key determinant of stock market fluctuations.

## 4. Conclusion

This study investigates the volatility connectedness among 16 key industry indices in Vietnam using WTI crude oil futures data and stock price indices, revealing a highly interconnected market. The TVP-VAR model results indicate an average Total Connectedness Index (TCI) of 70.35 per cent, underscoring strong interdependence among industries. Technology emerges as the most significant transmitter of volatility, while the airline sector experiences the least spillover effects. Dynamic total connectedness peaked in 2010, gradually declined until 2019, surged again through 2021, and stabilized by 2023. Given this high interconnectedness, investors should adopt diversified, long-term strategies across industries to manage risk. Sectors such as technology, electricity, agriculture, and construction act as major transmitters, creating both risks and hedging opportunities. Logistics, media, security, mineral, retail, petroleum, and banking require careful portfolio positioning, while tourism, airlines, medical, postal, and insurance sectors—though less exposed to shocks—offer stability but remain vulnerable to external risks. Collaborating with financial advisors can enhance tailored asset allocation. For policymakers, the findings stress the need for stronger oversight, transparency, and disclosure, particularly in high-volatility sectors. Balanced sectors should be monitored to avoid mispricing, while net receivers such as tourism and insurance require resilience-building policies. Limitations include the sample's restriction to 16 industries, exclusion of macroeconomic and geopolitical factors, reliance on price-based measures, and use of monthly data. Future research should expand coverage, include alternative oil benchmarks, and employ high-frequency data.

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